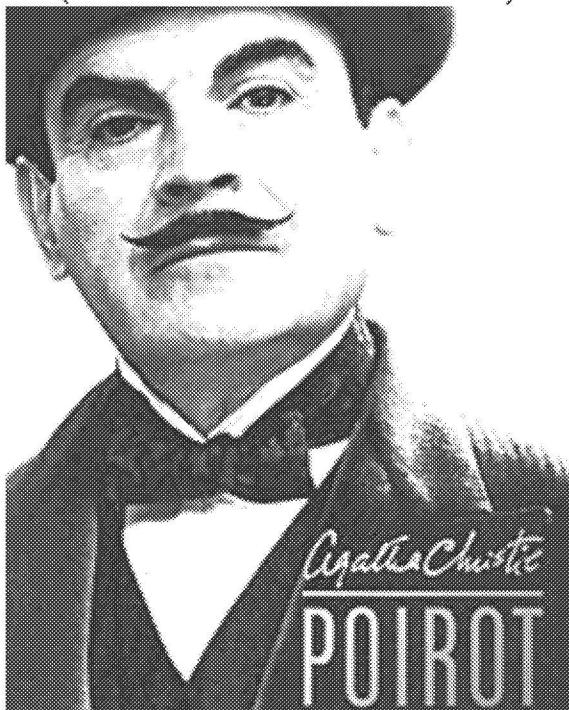


**Control Number :** GOOG-AT-MDL-008778351  
**All Custodians :** Ali Nasiri Amini, Nirmal Jayaram, Tim Lipus, Tobias Maurer  
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**Date/Time Created :** 4/11/2017 5:34 AM  
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**File Name :** Poirot launch  
doc\_1SqEfqq4fgf6nJfJQ4XmIN7  
WOEM0JpczzXVbBvIf4GuQ.docx

## Project Poirot

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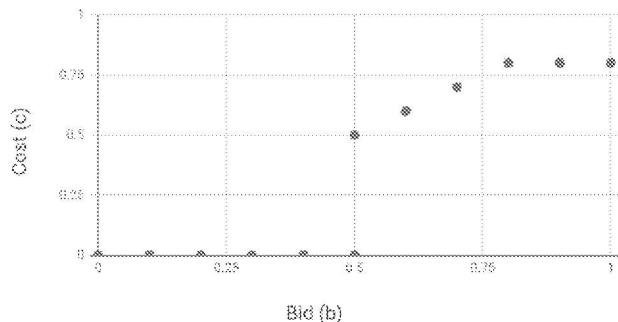
### Introduction

More than half of DBM's spend comes from non-Google-owned 3rd party exchanges. Many of these exchanges are known to run complex auctions that deviate from second pricing, in order to drive up the prices. This causes DBM advertiser performance to suffer. In this launch, we hope to address this by adapting our bidding to the non-second-priced nature of the auctions.

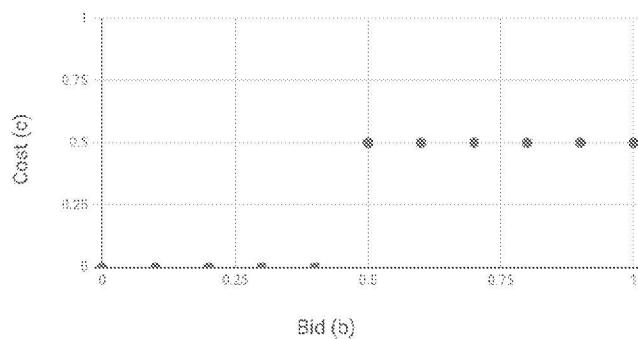
In a true second price auction, bidding low will sometimes cause us to lose an impression, but will never result in us winning the same impression cheaper. In a non-second-price auction, it is

sometimes possible to win the same impression cheaper. See the following illustrations of a second price and a non-second price auction.

Non second price auction



Clean second price auction



The ideal advertiser bid should be high enough to win the auction, but low enough to pay less for it. This lends itself to the following optimization metric.

Assumption: fixed CPM bidders assign a dollar value  $v$  (bid in the UI) for all impressions.

They have to pay a price  $c$  to the exchange to derive this value.

**The metric, surplus, is defined as  $v - c$**

Second price auctions optimize surplus in a trivial way: bid value  $v$ .

In non-second price auctions, we may have to bid  $< v$  to maximize surplus.

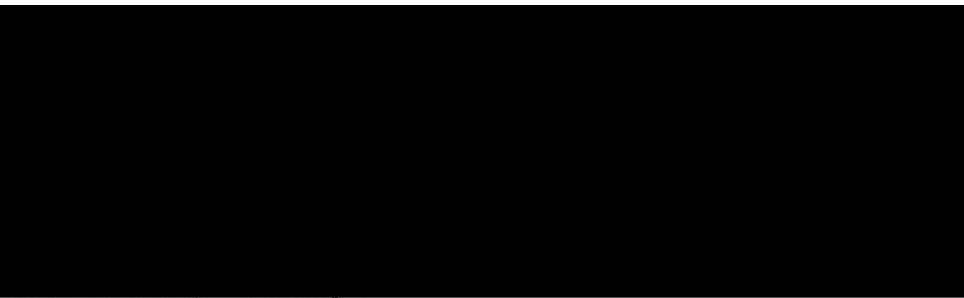
## Optimization methodology

We want to adjust bids to maximize surplus:

For each advertiser find bidding policy  $f(v, \text{query features})$  such that we Maximize  $\sum(v - c)$

- ➊ we started out with  $f(v, \text{query features}) = \alpha(\text{exchange}) \times v$
- ➋ in order to solve this optimization, we need to know how different  $\alpha$ 's affect the surplus
- ➌ hence, we setup exploration experiments using various values of  $\alpha$

The surplus change is assumed to take a quadratic form with the bid, where the surplus potentially increases for small reductions in bid due to price drop, reaches a maximum value (could happen at the original bid), then drops with further bid increases due to impression loss.



**Commented [1]:** why does it need to be a per advertiser model?

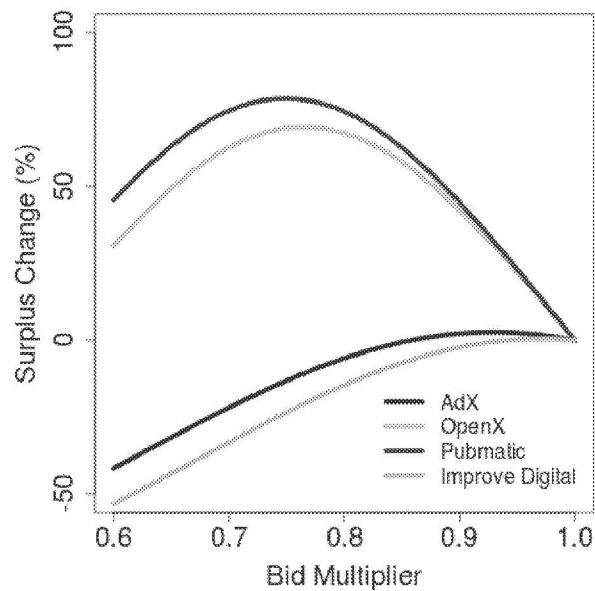
**Commented [2]:** It will be bad to have a great launch that affects Netflix really badly. It's safer to optimize this per advertiser as a result. The plan is to throw in more features in the future launches anyway to make this better.

**Commented [3]:** This is a bit confusing - it makes it seem like we are launching something that's just per-exchange (although you talk about advertiser below)

**Commented [4]:** @nirmaljayaram@google.com  
@ajaybangla@google.com

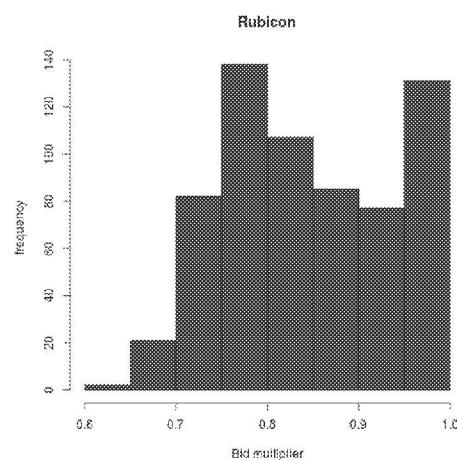
Is \alpha a function or a scalar? should I think of it as just a per-exchange weight?

**Commented [5]:** the original version had a per exchange \* advertise alpha (scalar per exchange \* advertiser). If the advertiser was too small, the model would automatically fallback to the exchange weight like Ajay was describing the other day.



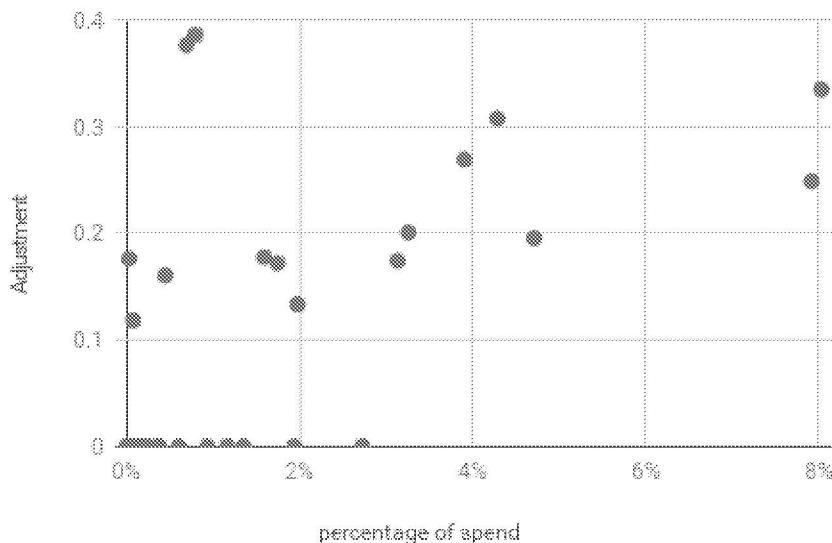
The plot below shows the histogram of bid multipliers at the advertiser level on the exchange Rubicon.

#### Rubicon



This chart shows the exchange priors for all the exchanges as a function of how much DBM spend comes from that exchange. We do not make any assumptions about the auction type of any exchange, and this is entirely arrived at algorithmically.

Adjustment vs. percentage of spend



Clicks PD: +4%  
Activeview rate: neutral  
Video completion rate: neutral  
Brand safety metrics: neutral